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Artificial Intelligence in Purchasing: Facilitating Mechanism Design-based Negotiations

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ABSTRACT
Negotiations are central to reach consensus between supply chain partners while, simultaneously, meeting internal cost and quality targets. Purchasing prices can be improved by inducing competition in the supply base. In this context, the application of mechanism design theory in negotiations gained enhanced attention. While such approaches can result in high cost reductions, mechanism design-based negotiations are very complex. The paper aims at answering the question whether artificial intelligence (AI) can facilitate the execution of mechanism design-based negotiations. To this end, a World Café has been conducted at an automotive original equipment manufacturer. A group of 20 experts from the fields of purchasing and AI discussed the potentials of AI for the purchasing function. The results indicate that the application of AI can indeed facilitate the execution of mechanism design-based negotiations and help overcoming bounded rationality problems. Even more, AI might be a game changer for the purchasing function.

Introduction: Could Artificial Intelligence Support the Design and Execution of Complex Negotiations?

Artificial intelligence (AI) is considered to be one of the pacemaker technologies of the 4$^{\text{th}}$ industrial revolution (Monostori 2014). With AI's promise to simulate human-like behavior (Russell and Norvig 2010), it could conceptionally be imagined to support complex problems like negotiations. Given the importance of business-to-business negotiations, previous research has focused on various influencing factors in the negotiation process as well as their outcomes. However, literature concentrating on how negotiations are executed remains scarce (Geiger 2017). Recent studies have tried to take up on this gap by addressing buying organizations' application of mechanism design theory in negotiations (e.g Huang et al. 2013; Schulze-Horn et al. in press).

Mechanism design theory represents the inverse of game theory: the development and implementation of economic incentives – so-called mechanisms – can lead to the achievement of desired objectives (Nisan

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2007; Varian 2011). In the realm of purchasing and supply management (PSM), industrial purchasers – as the mechanism designers – use this idea to develop negotiation rules that breed competition among suppliers and provide them with incentives to reduce their quotations (Berz 2014; Rieck, Drozak, and Von Grawert 2015).

Negotiating with the help of mechanism design theory takes root in many buying organizations (Berz 2014; Rieck, Drozak, and Von Grawert 2015). At the same time, however, the development of negotiation rules requires deep knowledge in economics. The negotiation design usually consists of several interdependent phases, each one combining various negotiation elements, such as auctions and exclusive offers, with a variety of incentive systems, e.g. supplier rankings, and information feedbacks (Schulze-Horn et al. in press). Consequently, the development of negotiation designs is a complex task. Assuming that purchasers are usually not specialized in this field, another difficulty is that individuals' rational decision-making is limited by their cognitive abilities, available information to solve decision problems, and the finite amount of time to reach decisions (Simon 1955). This bounded rationality results in a limited search process when developing negotiation rules – individuals tend to develop satisficing instead of optimizing solutions (Gigerenzer and Selten 2002; Simon 1956). According to Simon (1955, 101), "actual human rationality-striving can at best be an extremely crude and simplified approximation to the kind of global rationality that is implied, for example, by game-theoretic models".

To confront the problem of bounded rationality, previous research has suggested to enhance human decision-making performance with the help of AI (Dixon 2001; Moss 1992; Simon 1997). AI aims at developing machines with human-like problem solving skills (Russell and Norvig 2010). These machines possess a vast amount of computational capabilities. AI approaches are increasingly used in the area of negotiations. For instance, Leu, Hong Son, and Hong Nhung (2015) developed a Bayesian Fuzzy Game Model for construction procurement negotiations in order to help contractors to predict suppliers' bidding strategies and support them in determining appropriate bid prices. A fuzzy expert system was developed by Lin, Chen, and Chu (2011) to remove the time limitation in online auctions. AI might also support the execution of game-theoretic negotiation approaches. Accordingly, the following research question has been developed: *Could artificial intelligence facilitate the application of mechanism design-based negotiations?*

To answer this research question, a World Café has been executed at a European automotive original equipment manufacturer (OEM) with several years of experience in conducting mechanism design-based negotiations. Throughout open discussions with mixed groups of experts from the fields of PSM and AI, potential applications of AI in the purchasing process in general and in mechanism design-based negotiations in particular have been identified. The study at hand makes three important contributions. First, the

World Café findings confirm that purchasers do normally not possess sufficient knowledge in economics and game theory to develop sophisticated negotiation rules. Combined with resource restrictions, satisficing negotiation designs are developed, potentially leaving cost reductions untapped. Second, a vast amount of ideas concerning application possibilities of AI in the purchasing function have been generated. Thus, this new technology could be a game changer, leading to a shift in negotiation power to the benefit of buying organizations. Third, the success of applying AI technologies significantly depends on the amount and quality of available data. In the case of mechanism design-based negotiations, experience is still scarce, implying the need for expert systems. Machine learning approaches might be more relevant for purchasing activities for which considerable data bases exist, e.g. the analysis of suppliers' cost-breakdowns or the identification of patterns in suppliers' bids.

This paper is structured as follows: First, a theoretical background on mechanism design theory and its application in purchasing is provided. Next, an introduction to AI and two prominent branches of AI – expert systems and machine learning – is given. Subsequently, the World Café methodology is explained, followed by the study's results and a discussion thereof. The paper concludes with implications for theory and practice as well as limitations and a research agenda for the future.

The Application of Mechanism Design Theory in Purchasing

Mechanism Design Theory: Designing Incentives to Achieve Desired Outcomes

Many scholars have realized purchasing's eminent impact on the bottom line's performance of large industrial organizations (Schiele et al. 2011; Wynstra 2016). Especially in times of decreasing depth of value added, suppliers become more important and powerful (Pulles, Veldman, and Schiele 2014). Hence, scholars and practitioners are seeking for advanced negotiation techniques to increase the organization's profitability (Metty et al. 2005). In this context, previous research has shown that mechanism design theory can help to make negotiations more effective (e.g Huang et al. 2013; Prasad and Rao 2014; Schulze-Horn et al. in press).

Mechanism design theory, a branch of game theory, suggests the design and implementation of economic incentives to reach desired outcomes (Wang, Wu, and Liu 2010). Mechanism design theory can be regarded as the inverse of game theory (Singh and O'Keefe 2016). Game theory analyzes interactions between rational players whose decisions influence each other's actions (Lasaulce and Tembine 2011; Myerson 1991; Young 1991). Optimal outcomes of these interactions are identified and strategies are devised

stipulating how the players can achieve these outcomes (Lasaulce and Tembine 2011; Luce and Raiffa 1989). Game theory is built on two key assumptions. First, players are rational, implying that they behave self-interestedly (Jackson 2001; Myerson 1991). Second, interactions are defined by a set of rules which prescribe the players' potential actions and their associated outcomes (Colman 2008). Mechanism design theory, in contrast, does not take the rules of the game as given (Dash, Jennings, and Parkes 2003; Roth 2002). Here, the starting point represents a desired outcome of an interaction; then, mechanisms are designed that influence the players' behavior in such a way that a desired outcome is achieved (Han et al. 2012; Hehenkamp 2007; Maskin 2008).

Applying Mechanism Design Theory in Purchasing to Achieve Lower Quotations

According to Young (1991), a negotiation represents a decision-making process in which the actions of the parties involved affect each other mutually. Hence, negotiations can be regarded as games. In traditional bilateral negotiations, the rules of interaction are defined weakly, each party tries to behave strategically to maximize its own pay-off (Jackson 2001; Young 1991). In light of this, mechanism design theory can be applied in order to design the negotiation rules upfront. Such sophisticated negotiation rules, made transparent to all participating suppliers, can help to increase the perceived competitive pressure between suppliers (Kaufmann and Carter 2004). Previous research has shown that increased rivalry can lead to lower purchasing prices (Chen and Zhang 2011; Scheffler, Schiele, and Horn 2016). Mechanism design-based negotiations recently received growing interest due to their potential to result in significant cost savings (Drozak Consulting 2014; Schulze-Horn et al. in press).

The underlying rationale of mechanism design-based negotiations is to incentivize suppliers to disclose their least acceptable agreement, i.e. incentives aligned to the negotiation situation are designed to reveal the suppliers' reservation prices. In the study of Roth (2002), mechanism design theory is compared to the subject of engineering because – like an engineer – the mechanism designer is striving to generate mechanisms by exploiting trade as an instrument. Such game-theoretic negotiation designs consist of several interdependent phases (Schulze-Horn et al. in press). Each phase, in turn, comprises negotiation elements that are linked to a variety of incentive systems to motivate suppliers to lower their quotations. The selection of appropriate negotiation elements is crucial to the success of the entire negotiating situation: the effectiveness of elements such as auctions, re-quotes, and exclusive offers combined with incentives such as rankings, qualifications, privileges, and the final awarding depends on price dispersion

between the suppliers' quotes and awarding premises. Price dispersion represents an indicator of competitive intensity (Scheffler, Schiele, and Horn 2016; Vos et al. 2016), while awarding premises are preconditions stipulated by the buying organization for awarding the contract, for instance specifications concerning share allocations or single/multiple source requirements. For instance, the selection of appropriate auction modes depends, among others, on the price dispersion between the suppliers' quotes. Auctions with increasing prices, so-called Dutch auctions, are more effective than auctions with decreasing prices if there is a single supplier with an offer which is significantly lower than his competitors' bids (Güth, Ivanova-Stenzel, and Wolfstetter 2005; Samuelson 2002).

Despite the negotiation method's promising outcomes, there is a key drawback: the conceptualization of negotiation designs is very complex. It requires the resources to thoroughly analyze the negotiating situation. Additionally, expert knowledge in mechanism design theory is needed to derive conclusions regarding the selection of appropriate negotiation elements that can help to increase the competitive intensity between suppliers. Another issue is the fact that purchasers (and individuals in general) have only restricted capabilities of making rational decisions due limited cognitive abilities, limited information, and limited time to reach decisions (Simon 1955). According to Gigerenzer and Selten (2002, 5), "(a) key process in bounded rationality is limited search". Thus, individuals tend to settle for sub-optimal solutions. Taken everything together, the complexity of mechanism-design based negotiations potentially prevents a large-scale application of this negotiation approach.

Artificial Intelligence: The Imitation of Intelligent Human Behavior by Machines

Various scholars have attempted to define AI but the many facets and the scope make it difficult to find a universal definition. Most researchers agree that AI is a machine that simulates the human mind and thus acts intelligently (Adams et al. 2012; Haugeland 1989; McCarthy and Hayes 1969; Russell and Norvig 2010). Constituting an area of computer science, AI is thus concerned with the automation of human cognitive functions (Luger 2009). In this context, intelligence can be defined as "the ability to learn and understand, to solve problems and to make decisions" (Negnevitsky 2005, 2). Prominent examples of AI applications include autonomously driving cars, computer programs capable of beating humans in highly complex games (e.g. Google DeepMind's AlphaGo), and Apple's personal assistant Siri. According to McCarthy et al. (2006, 12), mimicking the human mind is possible since "(…) every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it." This implies that AI relies on the availability of data to learn from (Bini 2018).

The field of AI has many branches, including vision systems, language processing, robotics, expert systems, and machine learning. The latter two branches of AI seem potentially very useful for the purpose of facilitating mechanism design-based negotiations.

Expert systems represent highly knowledge-intensive computer programs who mimic the behavior of human experts (Nayak and Padhye 2018). Such systems apply problem-solving strategies that are built upon the knowledge of human experts of a certain domain. Expert knowledge combines the theoretical underpinnings of a problem with a set of heuristics to solve the problem (Luger 2009). Heuristics are rules that are based on the expert's professional expertise, past experience and/or judgment (Nayak and Padhye 2018). The simplest way of coding such rules is the IF/THEN form, consisting of a condition (IF) and an action (THEN) (Negnevitsky 2005). The expert's knowledge is coded in the form of heuristics which are stored in the knowledge base; the interference engine searches and interprets these heuristics in order to apply them to similar problems (Luger 2009; Nayak and Padhye 2018).

Being confronted with similar problems over and over again, expert systems however do not directly incorporate previous solutions, i.e. they do not learn (Luger 2009). Computer programs that are able to learn rules on their own, based on past experiences, analogies, examples, rewards or punishments, build on machine learning: their performance improves over time (Negnevitsky 2005; Obermeyer and Emanuel 2016). Jordan and Mitchell (2015, 255) define a learning problem as "the problem of improving some measure of performance when executing some task, through some type of training experience". The authors explain such a learning problem taking the example of detecting credit card fraud: The task involves the evaluation of credit card transactions as fraudulent or not; performance is assessed based on the accuracy of the evaluation; and the training is conducted with the help of historic data of credit card transactions which has been categorized as either fraudulent or not. For machine learning to work, learning algorithms need to be developed that allow computer programs to identify data patterns, and then to apply these patterns to make decisions or to predict future data (Murphy 2012). Machine learning applications increased rapidly over the past few years – a key driver for this phenomenon is a data deluge resulting from the significant amount of data that is constantly generated nowadays (Qiu et al. 2016).

Given the complexity of mechanism design-based negotiations, the idea emerged that AI might also facilitate this type of negotiation method. Previous research suggests that strong connections exist between game theory and AI (Tennenholtz 2002). Both research fields are concerned with decision theory and assume players to be rational (Elkind and Leyton-Brown

2010; Russell and Norvig 2010). Computer scientists began to study game theory in the 1990 s due to two major reasons: first, the computational properties of economic systems became too complex for practical use so that economics needed to collaborate with computer scientists, and second, the advances of the Internet required computer scientists to deal increasingly with settings in which players interact and thereby influence each other (Elkind and Leyton-Brown 2010; Parkes et al. 2010). Algorithmic game theory constitutes the research area resulting from the combination of game theory and AI (Nisan 2007). Three key research areas in algorithmic mechanism design concern game playing, social choice, and mechanism design (Elkind and Leyton-Brown 2010). With the help of AI methods, it is believed that also mechanism design-based negotiations could be supported by reducing the dependence on experts in this field of study, developing more sophisticated negotiation designs, shortening the preparation time for negotiations, and facilitating a large-scale application of the negotiation method. The ultimate result is higher cost savings for buying organizations.

Methodology: The World Café as an Exploratory Method for Qualitative Research

Discovering New Insights at the Intersection of Game Theory and AI through a World Café

Although this paper is not the first one to combine the research areas of game theory and AI (Elkind and Leyton-Brown 2010), application possibilities of AI in mechanism design-based negotiations have not been studied until now. For this reason, a qualitative research setting in the form of a World Café has been chosen. A World Café is a special form of focus group research (Ritch and Brennan 2010). Focus groups in general gained increased popularity as data collection tool in diverse research contexts over the past years (Carey and Asbury 2016). In the field of PSM, World Cafés are also often encountered as the method of choice (see e.g. Hüttinger et al. 2014; Pulles et al. 2016; Pumpe and Vallée 2017).

The general set-up of a World Café is as follows (see e.g Hoffmann 2011; Pumpe and Vallée 2017): Before the World Café starts, the research team pre-defines several topics that are to be discussed at different tables. The World Café sets off with a general introduction into these topics; then, the participants gather in small groups at the tables. Each discussion is guided by a moderator who also summarizes the research results. After each discussion round, the participants randomly join another discussion table. The moderator gives a short overview of the previous discussion outcomes. Then, the group builds upon these results while advancing its discourse. At the end of the World Café, each participant should have visited each discussion table.

Given this approach, World Cafés allow to gather comparatively large samples in a short time period; usually, a World Café takes less than a day to conduct (Hoffmann 2011; Tan and Brown 2005). Often, participants are asked to prioritize findings in the end (see e.g. Hoffmann, Schiele, and Krabbendam 2013; Pulles et al. 2016).

World Cafés are especially suited to explore new research topics by creating a comfortable, café-like atmosphere for the research participants that encourages casual, but meaningful conversations (Hüttinger et al. 2014; Pagliarini 2006). Such a research setting is especially useful since this study lies at the intersection of game theory, AI, and PSM. The World Café provides the opportunity to bring experts from these fields together and to let them exchange with each other during an open discourse.

According to Pulles et al. (2016), the World Café method provides two distinct advantages over focus groups and other qualitative research approaches: First, the participants in a World Café are regarded as co-researchers who explore the topic under study during several discussions together with academics. Instead of being interviewed in a (semi-)structured way, the participants actively spur each other on and engage in lively conversations. Second, the World Café explores topics of interest during several iterative discussions. In this way, the participants evaluate and build their further discourse upon previous discussion outcomes of their peers. "These multiple rounds of discussion allow the participants to confirm, sharpen, or reject the findings of their preceding discussions, thereby increasing the robustness of the World Café outcomes" (Pulles et al. 2016, 132).

Exploring Application Possibilities of AI in Mechanism Design-based Negotiations with Experts from an Automotive OEM

The study at hand was conducted at a European automotive OEM which has several years of experience in conducting mechanism design-based negotiations. Twenty experts who either belonged to the field of PSM or AI were brought together for a World Café session. All participants were from the case company or in strong relations with the case company (e.g. consultancies). Each table was dealing with a specific question related to the application of AI in purchasing in general as well as in mechanism design-based negotiations in particular. After reviewing literature for the two main underlying subjects of this study, i.e. mechanism design-based negotiations in the purchasing function as well as AI, four discussion topics were developed: (1) AI in the purchasing process, (2) AI in mechanism design-based negotiations, (3) implementation of AI in mechanism design-based negotiations, (4) future skills: impact of AI on the purchasing function. The underlying rationale of topic 1 was to identify general opportunities for the application of AI in the purchasing process, i.e. the discussion at Table 1 was not restricted to the actual negotiation part of the purchasing process. Rather it was

intended to create an open atmosphere in order to allow the discussants to develop creative ideas of how AI could make the purchasing process more effective and efficient. In contrast, the discussion taking place at Table 2 was clearly focused on the question of how AI could specifically support the preparation and execution of mechanism design-based negotiations. Table 3 was concerned with the concrete implementation of AI in mechanism design-based negotiations. Here, the experts were motivated by the moderator to think about the steps that would need to be undertaken as well as the preconditions to apply AI techniques in mechanism design-based negotiations. Finally, Table 4 again was a rather broad topic where the participants were invited to share their expectations about the impact of AI on the skill set that purchasers will need in the future.

The World Café started with a general introduction held by the research team. The presentation first familiarized all participants with the World Café methodology. Then, short introductions were provided into three topics: the purchasing process in general, mechanism design based-negotiations in particular, and AI. Afterward, the twenty participants randomly gathered in groups of 5 people at the discussion tables. Altogether, four discussion rounds were conducted. The first discussion round took 40 minutes, subsequent rounds were shorter with 30 minutes for the second and third round, and with 25 minutes for the last round. Finally, all participants as well as the research team gathered in a plenary session again. The moderators of the four discussion tables presented the outcomes which were gathered on flipcharts. Then, all participants were invited to rate the ideas by assigning points in order to identify the most promising insights. To this end, the purchasing and AI experts received stickers of different colors to be able to differentiate between the two expert groups. The participants were allowed to attach more than one sticker per outcome. Before closing the World Café, the participants had the opportunity to indicate whether they were missing any results; yet, all experts felt that the outcomes were comprehensive. An overview of the World Café set-up can be found in Figure 1.

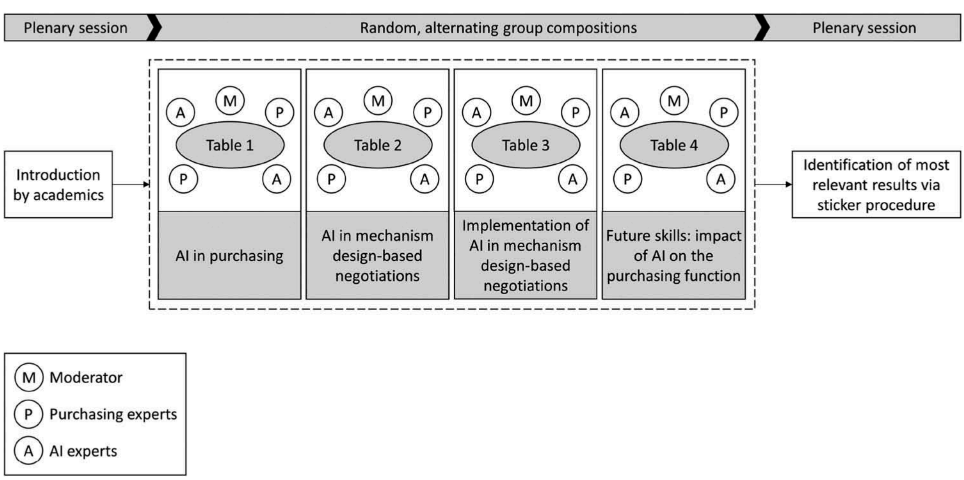

Figure 1. Overview World Café set-up.

After collecting the information from the experts during the World Café session, the data has been processed and analyzed. The actual analysis was based on the discussion points that were written down during the session by the moderator of each table as well as the audio recordings of the discussions, which were taken during the discussion rounds. The points on the flipcharts provided the basis of the analysis, the audio recordings were used to verify the discussion points. Overall, the data has been analyzed in a descriptive way rather than with the help of statistical tests.

Results: AI Applications Could Have a Significant Impact on the Purchasing Function

During the World Café session, discussions were held at four tables, covering four different topics concerning the application of AI in purchasing in general and in mechanism design-based negotiations in particular. In the results section, the main outcomes of each table and also the associated expert ratings are presented. As there were a lot of ideas developed, only those ideas for each table are detailed that were responsible for approximately 50% of the cumulated points that were assigned by the experts. By doing so, a focus lies on the most promising results. An overview of all ideas developed during the World Café can be found in the Appendix.

Topic 1 – AI in the Purchasing Process

The first discussion table was concerned with the identification of possible AI solutions in the entire purchasing process. The results are presented in the short list which is displayed in Table 1. The columns "Points assigned by AI experts (in %)" and "Points assigned by PSM experts (in %)" display the relative amount of points assigned to the discussion points by the two expert groups respectively. While the original list included 22 discussion points, the short-list contains four ideas that account for 52% of the points assigned by the experts. For the first discussion table, the following ideas were prioritized:

(a) ***Cost-optimizing engineering***: AI might help during the engineering stage or the early phase of the purchasing process to identify changes in the product that do not impair the functionality or the quality of the item under consideration but reduce the purchasing costs, e.g. through lower material costs or the avoidance of over-engineering.

(b) ***Analysis of cost-breakdowns***: The cost-breakdowns provided by the suppliers could be evaluated systematically and intelligently to detect hidden cost drivers. Additionally, a database could be created that contains detailed information concerning the cost structure of each supplier.

(c) ***Recognition of price patterns***: AI could identify patterns that reflect the development of commodity or material prices over time. As a result, optimal and anticyclical points of time for the sourcing process could be identified.

(d) ***Analysis of negotiation behavior:*** AI could be used to analyze the individual negotiation behavior of each supplier to predict how the supplier will behave in the negotiation process.

Table 1. Results topic 1 (AI in the purchasing process).

Discussion points	Points assigned by AI experts (in %)	Points assigned by PSM experts (in %)	Total points assigned (in %)
1. Cost-optimizing engineering	20%	14%	16%
2. Analysis of cost break downs	7%	18%	14%
3. Recognition of price patterns	4%	17%	12%
4. Analysis of negotiation behavior	7%	13%	10%
Rest of discussion points assigned to other topics	*62%*	*38%*	*48%*

Topic 2 – AI in Mechanism Design-based Negotiations

The second discussion table aimed at identifying opportunities for AI to support mechanism design-based negotiations. The results of the discussion and the subsequent ratings are presented in Table 2, which is a short list, consisting of those three ideas (out of 13) that gained the most interest, i.e. 58% of the expert ratings.

(a) ***Analysis of negotiation behavior:*** AI could be used to analyze the individual negotiation behavior of each supplier to predict how the supplier will behave in the negotiation process.

(b) ***Simulation of negotiations:*** AI could analyze the negotiation design of an upcoming negotiation and make predictions on the expected outcomes as well as validity checks of the suggested negotiation rules.

(c) ***Development of negotiation designs:*** AI autonomously develops negotiation designs that fit to the individual circumstances of each sourcing project and its market conditions.

Table 2. Results topic 2 (AI in mechanism design-based negotiations).

Discussion points	Points assigned by AI experts (in %)	Points assigned by PSM experts (in %)	Total points assigned (in %)
1. Analysis of negotiation behavior	27%	21%	23%
2. Simulation of negotiations	15%	21%	19%
3. Development of negotiation designs	18%	15%	16%
Rest of discussion points assigned to other topics	*40%*	*43%*	*42%*

Topic 3 – Implementation of AI in Mechanism Design-based Negotiations

The third discussion table was concerned with the technical implementation of AI in the process of conducting a mechanism design-based negotiation. The short list (Table 3) consists of those five ideas (out of 15) that account for 52% of the expert ratings.

(a) ***Simulation of negotiations:*** AI could analyze the predefined rules of an upcoming negotiation and make predictions of the expected outcomes as well as validity checks of the suggested negotiation design.
(b) ***Expert systems:*** Expert systems that aim at imitating human knowledge and behavior could be developed. In the first step, these systems would still require human input and interaction. With an increasing amount of data available, the systems could become more intelligent through machine learning approaches and ultimately make the human input obsolete.
(c) ***Information seeking across systems:*** AI could be capable of collecting meaningful data from the various IT systems of large buying organizations and to intelligently merge these data in a way that they facilitate the process of conducting mechanism design-based negotiations.
(d) ***Heuristic mechanism design selection:*** If there are too many and partially conflicting goals and targets of a negotiation, the degrees of freedom might be too high in order to be able to develop one single solution. Heuristic selection systems, supported by AI, might compare the expected outcomes of each proposed negotiation design and then choose the most suitable one. This process could be repeated in various rounds and would result in the survival of the fittest design.
(e) ***Goal definition:*** A precondition for designing negotiation rules is to define goals and premises a priori. So far, the complexity of the goals that can be taken into consideration is somewhat limited by human cognitive capacities. AI could make it possible to include a larger number of goals in the process of designing negotiation rules by providing the amount of cognitive capacity that is needed to do so.

Table 3. Results topic 3 (Implementation of AI in mechanism design-based negotiations).

Discussion points	Points assigned by AI experts (in %)	Points assigned by PSM experts (in %)	TOTAL POINTS ASSIGNED (IN %)
1. Negotiation simulations	15%	19%	17%
2. Expert systems	8%	11%	9%
3. Information seeking across systems	3%	16%	9%
4. Heuristic mechanism design selection	15%	3%	9%
5. Goal definition	10%	5%	8%
Rest of discussion points assigned to other topics	*49%*	*46%*	*48%*

Topic 4 – Future Skills: The Impact of AI on the Purchasing Function

The fourth table covered the topic of future skills that are likely to be relevant for the purchasing function as a consequence of the ongoing trend toward an application of AI in business operations. Since the topic of the fourth table was on purpose very open and not directly related to the central research question of this study, expert ratings were not analyzed for the fourth table. Among the discussants, there was a broad consensus that the increasing reliance on AI has two implications. There will be a transformation in the nature of the purchasing function and also the requirements on the purchasing staff will evolve in the future. As a consequence, three fields of action have been identified that should be considered when implementing AI in the purchasing function:

(a) ***Coaching interaction of humans and AI:*** In the future, it might become more important that humans interact with AI. In this case, it will be necessary to train the purchasing staff how (and when) to rely on AI in general.
(b) ***Training in systems:*** If specific applications or systems are developed, the purchasing staff will need training in these specific systems.
(c) ***Building trust in AI:*** As AI is still a rather new theme in business operations, it might create some uncertainties among the purchasing staff how their job profile will be affected in the future and how reliable AI applications are. Accordingly, organizations should dedicate some resources to create trust in this new technology.

Discussion: Prospects of Success Substantially Depend on Data Availability

In this section, the previously presented results will be discussed in more detail. The topic of the first discussion table was about potential areas of application of AI in the entire purchasing process. The results indicate that the AI experts see the biggest potential in the application of AI already during the development stage of the product life cycle. By doing so, AI could support the engineer to take cost parameters into account when designing a product. For instance, AI could suggest alternative materials with comparable characteristics that are cheaper than the originally intended ones. The idea of engineering products in a cost-efficient manner is a widely accepted sourcing lever (see e.g. Hesping and Schiele 2016; Schiele 2007; Schiele et al. 2011). Schiele et al. (2011) even find in their study that product optimization is expected to result in the highest cost savings of the analyzed sourcing levers. Likewise, also in the domain of engineering, it is acknowledged that AI can be used to support the product development process (see e.g. Kwong, Jiang, and Luo 2016; Pham and Pham 1999; Yan Chan et al.

2016). Hence, there seems to be a good match between an idea that can contribute to an improved purchasing performance and the applicability of AI. Another potential application of AI in the purchasing process has been identified as the analysis of cost breakdowns. In many large buying organizations, the suppliers that are interested in being awarded with a sourcing contract are asked to submit a detailed cost breakdown. In these cost breakdowns, the suppliers disclose their entire cost structure which subsequently is verified by a cost expert from the buying organization. The purchasing experts suggest that the data in the cost breakdowns is very valuable for the negotiation process, as main cost drivers can be identified and mitigated (Ellram 2000). At the case company, however, the information contained in cost breakdowns is neither stored nor processed in a systematic way, since this would require a vast amount of additional capacities. By means of using AI for the analysis and systematic processing of the data, a powerful tool could be created, entailing supplier specific cost data that could be stored in a supplier folder. Being able to retrieve this data would facilitate the job of the purchaser in various ways, e.g. for the preparation of the negotiation. Similarly, the experts indicated that AI could be used to identify cost patterns, i.e. to make predictions how the costs are likely to evolve over time. From a technical perspective both ideas seem to be feasible (Michalski, Carbonell, and Mitchell 2013). The idea to benefit from the systematic storage and analysis of supplier specific data was also mentioned in the context of the identification of individual negotiation patterns. The underlying rationale is that every supplier might have individual traits when it comes to the negotiation process. Previous research demonstrates that it is indeed possible to draw inferences from the supplier's behavior from past transactions (Ray, Jenamani, and Mohapatra 2011). AI applications could provide the respective cognitive capabilities and resources to make these predictions.

The idea to identify patterns in the behavior of suppliers was also addressed in the second discussion table, which investigated the potential of AI to support mechanism design-based negotiations. In this context, Ray, Jenamani, and Mohapatra (2011) describe how this behavioral aspect of the supplier can be used in reverse auctions for an efficient supplier selection. Furthermore, at the second discussion table, the idea emerged that AI could be used for simulations of forthcoming negotiations. The experts expressed the belief that a priori it could be tested whether a specific set of predefined negotiation rules actually leads to the intended outcomes. This approach could be connected with the prediction of the supplier specific negotiation behavior and the associated expected outcomes (Carbonneau, Kersten, and Vahidov 2011). Another potential field of application for mechanism design-based negotiations has been identified in the development of the rules for the negotiation. As mentioned earlier in this paper, the actual process of

developing the negotiation design is a very complex and challenging task. Incorporating effective incentives which motivate suppliers to improve their quotations requires high degrees of expert knowledge in game theory as well as considerable cognitive capabilities (Schulze-Horn et al. in press). This is also confirmed by an analysis of the World Café's audio recordings. Several of the invited PSM experts expressed their opinion that the complexity of mechanism design-based negotiations withholds them from applying this potentially very effective negotiation method. A tool that is able to reduce the complexity of mechanism design-based negotiations would therefore be highly appreciated. That AI can solve game-theoretic issues and translate them into negotiation designs is in line with scholars such as Jazayeriy et al. (2012).

So far, the discussions at Tables 1 and 2 have indicated that the purchasing function could benefit from the application of AI. At Table 3, therefore, the discussion was focused on the feasibility of these ideas, given the current state of the art in AI. Both expert groups agreed that the simulation of negotiations would be a strong enabler for the successful implementation of mechanism design theory in negotiations. From a technical perspective, it seems to be achievable. However, in general the expert groups also agreed that without sufficient data on previous mechanism design-based negotiations, expert systems are preferable which still require human input and training. By means of machine learning approaches in connection with growing data sets, the degrees of autonomy are indeed likely to rise but these systems are unlikely to make the human purchaser obsolete in the near future. The most realistic and achievable scenario would be the implementation of applications that are able to seek information across the borders of single IT systems. It can be argued that in particular large industrial organizations have in principle access to a rich set of highly relevant data. Unfortunately, the data are often spread across different IT systems and various business functions, making it almost impossible for the purchaser to identify all the relevant information. An AI application that can intelligently retrieve and merge information from diverse data sources would be a significant step forward to more effective purchasing processes. Additionally, it was discussed at the third table that even if the current state of the art in AI would not be able to automatically design the negotiation rules for complex sourcing projects, it should at least be realistic and feasible to apply heuristics in order to forecast the outcomes of a given set of negotiation rules. A precondition to do so would be the precise definition of the goals that shall be achieved during the negotiation process.

The fourth discussion table was concerned with the impact of AI on purchasing skills requirements. According to the experts' opinions, the nature of the purchasing function is likely to change, and as a result thereof, the requirements on the purchasing staff have to evolve in the future. This is in line with studies from Lichtblau et al. (2015) and Geissbauer, Vedso, and Schrauf (2016). Example from previous research show how AI can be applied

in the purchasing process. Leu, Hong Son, and Hong Nhung (2015) developed a Bayesian Fuzzy Game Model for construction procurement negotiations to help contractors predicting suppliers' bidding strategies and support them in determining appropriate bid prices. Other authors are concerned with the complete automation of negotiations (see e.g. Baarslag and Kaisers 2017; Lau 2007). Thus, it can be expected that purchasers need to take into account input from AI-based systems during negotiations or that they might even be able to leave the act of negotiating to machines. In these cases, purchasers could concentrate more on a thorough negotiation preparation, for instance through cross-functional coordination. Similarly, this change could also imply an increased need for knowledge in information technology, data security, and data analysis (Lichtblau et al. 2015).

Implications for Theory and Practice: AI Can Surmount Bounded Rationality but Purchasers Need Thorough Training in Using AI Technologies

Starting with the theoretical implications, the study confirms that the individual purchaser is lacking the expert knowledge in economics and game theory in order to be able to develop rules for a mechanism design-based negotiation. As already suggested by Selten (1991), humans are often exposed to bounded rationality. Due to restricted capabilities to reach rational decisions resulting from limited cognitive abilities, limited information, and limited time to reach decisions (Simon 1955), it is unlikely that all decision variables can be taken into consideration in order to design optimal negotiation rules. Balancing the effort to come to a rational conclusion with associated decision costs, a satisficing solution is often developed instead (Selten 1991). However, the results of this research paper point into the direction that AI can surmount the barriers to the application of mechanism design-based negotiations that arise due to cognitive constraints of the human nature. Moreover, the expert discussions also provide support for the research of Jazayeriy et al. (2012) who argue that AI already reached a stage of maturity that is sufficient to conduct autonomous negotiations based on game-theoretic insights. Additionally, it has been found that the application of AI is not limited to the purchasing function itself but could also be applied in adjacent functions, such as research and development in order to optimize product design with the aim to reduce purchasing costs (Schiele et al. 2011). Here, AI could support the product development process (see e.g. Kwong, Jiang, and Luo 2016; Pham and Pham 1999; Yan Chan et al. 2016), i.e. AIs could take into account cost parameters during the engineering stage and thereby design cost-efficient products.

Also from a managerial perspective, at least two strong implications emerge: a shift of power toward the buyer and substantial training needs for staff. Concerning the first implication, the World Café discussions highlight that

a significant amount of ideas exists how AI could enhance operations in the purchasing function. For instance, tools that predict suppliers' cost parameters with the help of cost-breakdowns or tools that analyze suppliers' negotiation behavior could lead to a drastic shift of negotiation power to the benefit of buying organizations. Thus, AI might be a game changer for the purchasing function. However, changing existing processes and systems can be an onerous and lengthy procedure in large, established organizations (Albert, Wehinger, and Fraterman 2017). Consequently, a timely reaction to and subsequent adoption of new technological trends is required in order to remain competitive or even take a pioneering position ahead of competitors. The second implication concerns the impact on purchasing staff. At the fourth discussion table, it has been debated how the application of AI is likely to affect the purchasing skills requirements. The results indicate that the nature of the purchasing function is expected to change in the future toward a more automated state, somewhat reducing the need for purchasers to carry out purely operative tasks. However, AI would be unlikely to replace purchasers' activities, rather complementing them as another tool. Hence, intensive training to use AI would be needed. This implies that the requirements on the purchasing staff have to evolve over time. It is probable that purchasing staff require coaching in the interaction with AI applications. In the near future, training seems relevant in the use of expert systems that are indeed partially intelligent but still require human input. Additionally, trust in the new way of working must be created. AI should not be seen as a rival or replacement of the human purchaser. Instead, it should be seen as a facilitator of a more effective and efficient purchasing function.

Limitations and Future Research: Developing a Research Agenda to Support the Transformation of the Purchasing Function

Despite the study's implications, several limitations of the research setting need to be acknowledged. AI applications in purchasing just recently started to emerge. Hence, the level of experience also of the experts is still rising. This potentially limits the innovativeness and confidence of their contributions during the World Café. The research has been conducted at only one case company from the automotive sector, partially limiting the generalizability of the results. Still, the automotive industry is of large importance for the world economy and often associated with pioneering and innovative approaches, making it a very popular research environment in PSM (Horn, Schiele, and Werner 2013; Vos et al. 2016). Another limitation could be seen in the fact that only a group of 20 participants served as sample for the study. The participants might have provided biased answers due to relationships with the case company or personal preferences regarding the topic. Still, the participants could confirm, sharpen, or reject the opinions of their peers in multiple rounds of discussion (Pulles et al. 2016). Additionally, the company

under consideration has several years of experience in the application of mechanism design-based negotiations. To date, industry benchmarks revealed that there is only a small number of corporations in the automotive sector with this extend of experience.

This paper concludes with a research agenda. The findings resulting from the World Café discussions may serve as a basis for further analysis in order to turn the experts' ideas into practical use. To this end, several topics require additional research in the future:

- AI technologies could change drastically the way in which purchasing tasks are executed. Concomitant, the skill sets of purchasing staff will change. To prepare for this potentially disruptive change, further research should analyze in greater detail the impact of new technologies on the purchasing function. Concrete recommendations for action can help to increase buying organizations' technological responsiveness, and in turn their future competitiveness.
- The research findings highlighted that – due to a lack of data – expert systems could be applied in the near future to facilitate mechanism design-based negotiations. To this end, it should be researched how optimal negotiation designs can be developed. Which negotiation elements can be applied? Under which circumstances are they most effective? How can these negotiation elements be aligned with incentive systems that motivate suppliers to offer cost reductions? Negotiation research would benefit from a revitalization and quantification, given the new technological opportunities.
- Introducing AI-based tools that negotiate automated and autonomously implies that a tool reaches decisions in which several million Euros are at stake. To what extent can buying organizations trust the decisions taken by AI? It is questionable if rational decisions taken by AI are always acceptable for buying organizations, e.g. the rational decision to get into business with a new supplier due to lower purchasing prices could mean that another supplier currently in business with the buying organization faces bankruptcy due to a loss of orders. Likewise, legal aspects of such decisions need to be carefully studied. In this regard, it should be researched how some kind of ethical, legal or strategic awareness can be incorporated in AI-based tools. Human decision-makers know about the context of their decisions. AIs would need to be instructed accordingly, too.
- This study focused on potential applications of AI by the purchasing function. It is reasonable to expect that likewise suppliers work on the introduction of advanced technologies. In this context, it is relevant to explore which application possibilities of AI suppliers see in the interaction with buying organizations. Taking the extreme case, the pure act of

negotiating prices might be automated by both parties in the long-term. In this scenario, how will prices be determined? Will the final quote depend on the effectiveness of the AI technologies in use? Will negotiation bots become so intelligent, e.g. with the help of analyses on suppliers' and purchasers' negotiation behavior or due to detailed cost forecasts based on suppliers' cost-breakdowns, that the act of negotiating becomes obsolete? Yet, autonomous negotiations could extend negotiations beyond mere price issues, and incorporate many more aspects relevant for closing a deal, such as quality requirements, service levels, product features, etc.

References

Adams, S., I. Arel, J. Bach, R. Coop, R. Furlan, B. Goertzel, J. Sowa, A. Samsonovich, M. Scheutz, and M. Schlesinger. 2012. Mapping the Landscape Of Human-Level Artificial General Intelligence. *AI Magazine* 33 (1):25–42. doi:10.1609/aimag.v33i1.2322.

Albert, T., J. Wehinger, and J. Fraterman. 2017. Die Beschaffung ist tot – Es lebe die Beschaffung [Procurement is dead - long live procurement]. In *Innovative Produkte und Dienstleistungen in der Mobilität: Technische und betriebswirtschaftliche Aspekte* [Innovative products and services in mobility: Technical and business aspects], ed. H. Proff and T. M. Fojcik, 51–66. Wiesbaden: Springer Fachmedien Wiesbaden.

Baarslag, T., and M. Kaisers. 2017. The value of information in automated negotiation: A decision model for eliciting user preferences. In *Proceedings of the 16th Conference on autonomous agents and multi agent systems*, ed. S. Das, E. Durfee, K. Larson, and M. Winikoff, 391–400. Richland, SC: International Foundation for Autonomous Agents and Multiagent Systems.

Berz, G. 2014. *Spieltheoretische Verhandlungs- und Auktionsstrategien: Mit Praxisbeispielen von Internetauktionen bis Investmentbanking* [Game theory bargaining and auction strategies: Practical examples from internet auctions to investment banking]. Stuttgart: Schäffer-Poeschel Verlag.

Bini, S. A. 2018. Artificial intelligence, machine learning, deep learning, and cognitive computing: What do these terms mean and how will they impact health care? *The Journal of Arthroplasty*,33 (8), 2358-2361.

Carbonneau, R. A., G. E. Kersten, and R. M. Vahidov. 2011. Pairwise issue modeling for negotiation counteroffer prediction using neural networks. *Decision Support Systems* 50 (2):449–59. doi:10.1016/j.dss.2010.11.002.

Carey, M. A., and J.-E. Asbury. 2016. *Focus group research*. London, New York: Routledge.

Chen, Y., and T. Zhang. 2011. Equilibrium price dispersion with heterogeneous searchers. *International Journal of Industrial Organization* 29 (6):645–54. doi:10.1016/j.ijindorg.2011.03.007.

Colman, A. M. 2008. *Game theory and its applications in the social and biological sciences*. London: Routledge.

Dash, R. K., N. R. Jennings, and D. C. Parkes. 2003. Computational-mechanism design: A call to arms. *IEEE Intelligent Systems* 18 (6):40–47. doi:10.1109/MIS.2003.1249168.

Dixon, H. D. 2001. Some thoughts on economic theory and artificial intelligence. In *Surfing economics: Essays for the enquiring economist*, ed. H. D. Dixon, 161-176. Basingstoke: Palgrave Macmillan.

Drozak Consulting. 2014. Spieltheorie im Einkauf [Game Theory in Procurement]. In *trend - drive for purchase, Q4*, 1–12. Berlin: Drozak Consulting GmbH.

Elkind, E., and K. Leyton-Brown. 2010. Algorithmic game theory and Artificial Intelligence. *AI Magazine* 31 (4):9–12. doi:10.1609/aimag.v31i4.2310.

Ellram, L. M. 2000. Purchasing and supply management's participation in the target costing process. *Journal of Supply Chain Management* 36 (1):39–51. doi:10.1111/j.1745-493X.2000.tb00076.x.

Geiger, I. 2017. A model of negotiation issue–based tactics in business-to-business sales negotiations. *Industrial Marketing Management* 64 (4):91–106. doi:10.1016/j.indmarman.2017.02.003.

Geissbauer, R., J. Vedso, and S. Schrauf. 2016. *2016 Global industry 4.0 survey - Industry 4.0: Building the digital enterprise*. PricewaterhouseCoopers.

Gigerenzer, G., and R. Selten. 2002. *Bounded rationality: The adaptive toolbox*. Cambridge, Massachusetts: The MIT press.

Güth, W., R. Ivanova-Stenzel, and E. Wolfstetter. 2005. Bidding behavior in asymmetric auctions: An experimental study. *European Economic Review* 49 (7):1891–913. doi:10.1016/j.euroecorev.2004.09.003.

Han, Z., D. Niyato, W. Saad, T. Basar, and A. Hjorungnes. 2012. *Game theory in wireless communications and networks: Theory, models, and applications*. Cambridge: Cambridge University Press.

Haugeland, J. 1989. *Artificial intelligence: The very idea*. Cambridge, MA: MIT Press.

Hehenkamp, B. 2007. Die Grundlagen der Mechanismus-Design-Theorie [The foundations of mechanism design theory]. *Wirtschaftsdienst* 87 (11):768–72. doi:10.1007/s10273-007-0732-z.

Hesping, F. H., and H. Schiele. 2016. Matching tactical sourcing levers with the Kraljič matrix: Empirical evidence on purchasing portfolios. *International Journal of Production Economics* 177:101–17. doi:10.1016/j.ijpe.2016.04.011.

Hoffmann, P. 2011. *Innovative supply risk management: The development of a comprehensive supply risk management system. Twente*. Enschede, NL: CPI Wöhrmann.

Hoffmann, P., H. Schiele, and K. Krabbendam. 2013. Uncertainty, supply risk management and their impact on performance. *Journal of Purchasing and Supply Management* 19 (3):199–211. doi:10.1016/j.pursup.2013.06.002.

Horn, P., H. Schiele, and W. Werner. 2013. The ugly twins: Failed low-wage-country sourcing projects and their expensive replacements. *Journal of Purchasing and Supply Management* 19 (1):27–38. doi:10.1016/j.pursup.2012.09.001.

Huang, H., R. J. Kauffman, H. Xu, and L. Zhao. 2013. A hybrid mechanism for heterogeneous e-procurement involving a combinatorial auction and bargaining. *Electronic Commerce Research and Applications* 12 (3):181–94. doi:10.1016/j.elerap.2013.03.006.

Hüttinger, L., H. Schiele, D. Schröer, and B. Wagner. 2014. Exploring the antecedents of preferential customer treatment by suppliers: A mixed methods approach. *Supply Chain Management: An International Journal* 19 (5/6):697–721. doi:10.1108/SCM-06-2014-0194.

Jackson, O. M. 2001. A crash course in implementation theory. *Social Choice and Welfare* 18 (4):655–708. doi:10.1007/s003550100152.

Jazayeriy, H., M. Azmi-Murad, N. Sulaiman, and N. I. Udzir. 2012. Generating pareto-optimal offers in bilateral automated negotiation with one-Side uncertain importance weights. *Computing and Informatics* 31 (6):1235–53.

Jordan, M. I., and T. M. Mitchell. 2015. Machine learning: Trends, perspectives, and prospects. *Science* 349 (6245):255–60. doi:10.1126/science.aaa8415.

Kaufmann, L., and C. R. Carter. 2004. Deciding on the mode of negotiation: To auction or not to auction electronically. *The Journal of Supply Chain Management* 40 (1):15–26. doi:10.1111/j.1745-493X.2004.tb00166.x.

Kwong, C. K., H. Jiang, and X. G. Luo. 2016. AI-based methodology of integrating affective design, engineering, and marketing for defining design specifications of new products. *Engineering Applications of Artificial Intelligence* 47:49–60. doi:10.1016/j.engappai.2015.04.001.

Lasaulce, S., and H. Tembine. 2011. *Game theory and learning for wireless networks: Fundamentals and applications*. Oxford: Academic Press.
Lau, R. Y. K. 2007. Towards a web services and intelligent agents-based negotiation system for B2B eCommerce. *Electronic Commerce Research and Applications* 6 (3):260–73. doi:10.1016/j.elerap.2006.06.007.
Leu, -S.-S., P. V. Hong Son, and P. T. Hong Nhung. 2015. Optimize negotiation price in construction procurement using Bayesian fuzzy game model. *KSCE Journal of Civil Engineering* 19 (6):1566–72. doi:10.1007/s12205-014-0522-2.
Lichtblau, K., V. Stich, R. Bertenrath, M. Blum, M. Bleider, A. Millack, … M. Schröter. 2015. *Industrie 4.0-readiness*. Aachen: IMPULS-Stiftung des VDMA.
Lin, -C.-C., S.-C. Chen, and Y.-M. Chu. 2011. Automatic price negotiation on the web: An agent-based web application using fuzzy expert system. *Expert Systems with Applications* 38 (5):5090–100. doi:10.1016/j.eswa.2010.09.142.
Luce, R. D., and H. Raiffa. 1989. *Games and decisions: Introduction and critical survey*. New York: Dover Publications.
Luger, G. F. 2009. *Artificial intelligence: Structures and strategies for complex problem solving*. Boston: Pearson Education.
Maskin, E. S. 2008. Mechanism design: How to implement social goals. *The American Economic Review* 98 (3):567–76. doi:10.1257/aer.98.3.567.
McCarthy, J., and P. J. Hayes. 1969. Some philosophical problems from the standpoint of artificial intelligence. In *Machine intelligence*, ed. B. Meltzer and D. Michie, 463–502. Edinburgh: Edinburgh University Press.
McCarthy, J., M. L. Minsky, N. Rochester, and C. E. Shannon. 2006. A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. *AI Magazine* 27 (4):12–14.
Metty, T., R. Harlan, Q. Samelson, T. Moore, T. Morris, R. Sorensen, J. Robbins, O. Raskina, R. Schneur, and J. Kanner. 2005. Reinventing the supplier negotiation process at motorola. *Interfaces* 35 (1):7–23. doi:10.1287/inte.1040.0119.
Michalski, R. S., J. G. Carbonell, and T. M. Mitchell. 2013. *Machine learning - An artificial intelligence approach*. Berlin Heidelberg: Springer Verlag.
Monostori, L. 2014. Cyber-physical production systems: Roots, expectations and R&D challenges. *Procedia CIRP* 17:9–13. doi:10.1016/j.procir.2014.03.115.
Moss, S. 1992. Introduction. In *Artificial intelligence and economic analysis: Prospects and problems*, ed. S. Moss and J. Rae, 1-10. Aldershot: Edward Elgar Publishing Limited.
Murphy, K. 2012. *Machine learning: A probabilistic perspective*. Cambridge: MIT Press.
Myerson, R. B. 1991. *Game theory: Analysis of Conflict*. Cambridge: Harvard University Press.
Nayak, R., and R. Padhye. 2018. *Artificial intelligence and its application in the apparel industry*. In R. Nayak & R. Padhye (Eds.), Automation in Garment Manufacturing (pp. 109-138). Duxford, UK: Woodhead Publishing.
Negnevitsky, M. 2005. *Artificial Intelligence: A Guide to Intelligent Systems*. Harlow: Pearson Education.
Nisan, N. 2007. Introduction to Mechanism Design (for Computer Scientists). In N. Nisan, T. Roughgarden, E. Tardos, & V. V. Vazirani (Eds.), Algorithmic Game Theory (pp. 209-242). Cambridge: Cambridge University Press.
Obermeyer, Z., and E. J. Emanuel. 2016. Predicting the future — Big data, machine learning, and clinical medicine. *The New England Journal of Medicine* 375 (13):1216–19. doi:10.1056/NEJMp1606181.
Pagliarini, R. R. R. 2006. The World Café shaping our futures through conversations that matter. *Journal of Organizational Change Management* 19 (2):266–68. doi:10.1108/09534810610648951.

Parkes, D. C., R. Cavallo, F. Constantin, and S. Singh. 2010. Dynamic incentive mechanisms. *AI Magazine* 31 (4):79–94. doi:10.1609/aimag.v31i4.2316.

Pham, D. T., and P. T. N. Pham. 1999. Artificial intelligence in engineering. *International Journal of Machine Tools and Manufacture* 39 (6):937–49. doi:10.1016/S0890-6955(98)00076-5.

Prasad, A. S., and S. Rao. 2014. A mechanism design approach to resource procurement in cloud computing. *IEEE Transactions on Computers* 63 (1):17–30. doi:10.1109/TC.2013.106.

Pulles, N. J., H. Schiele, J. Veldman, and L. Hüttinger. 2016. The impact of customer attractiveness and supplier satisfaction on becoming a preferred customer. *Industrial Marketing Management* 54:129–40. doi:10.1016/j.indmarman.2015.06.004.

Pulles, N. J., J. Veldman, and H. Schiele. 2014. Identifying innovative suppliers in business networks: An empirical study. *Industrial Marketing Management* 43 (3):409–18. doi:10.1016/j.indmarman.2013.12.009.

Pumpe, A., and F. Vallée. 2017. A typology for selecting an appropriate total landed cost method in international supplier selection decisions. *Transportation Research Procedia* 25:853–69. doi:10.1016/j.trpro.2017.05.462.

Qiu, J., Q. Wu, G. Ding, Y. Xu, and S. Feng. 2016. A survey of machine learning for big data processing. *EURASIP Journal on Advances in Signal Processing* 2016 (1):67. doi:10.1186/s13634-016-0355-x.

Ray, A. K., M. Jenamani, and P. K. J. Mohapatra. 2011. Supplier behavior modeling and winner determination using parallel MDP. *Expert Systems with Applications* 38 (5):4689–97. doi:10.1016/j.eswa.2010.08.044.

Rieck, C., J. Drozak, and G. Von Grawert. 2015. *Spieltheorie im Einkauf: Auktionen in Theorie und Praxis* [Game theory in procurement: Auctions in theory and practice]. Eschborn: Christian Rieck Verlag.

Ritch, E. L., and C. Brennan. 2010. Using World Café and drama to explore older people's experience of financial products and services. *International Journal of Consumer Studies* 34 (4):405–11. doi:10.1111/j.1470-6431.2010.00881.x.

Roth, A. E. 2002. The economist as engineer: Game theory, experimentation, and computation as tools for design economics. *Econometrica* 70 (4):1341–78. doi:10.1111/1468-0262.00335.

Russell, S. J., and P. Norvig. 2010. *Artificial intelligence - A modern approach*. Upper Saddle River: Prentice Hall.

Samuelson, W. F. 2002. Auctions in Theory and Practice. In K. Chatterjee & W. F. Samuelson (Eds.), Game Theory and Business Applications (pp. 295-338). Berlin-Heidelberg: Springer Verlag.

Scheffler, P., H. Schiele, and P. Horn. 2016. How to measure competition? The role of price dispersion in B2B supply markets. *International Journal of Procurement Management* 9 (5):568–86. doi:10.1504/IJPM.2016.078692.

Schiele, H. 2007. Supply-management maturity, cost savings and purchasing absorptive capacity: Testing the procurement–performance link. *Journal of Purchasing & Supply Management* 13 (4):274–93. doi:10.1016/j.pursup.2007.10.002.

Schiele, H.,Horn, P., & Vos, B. 2011. Estimating cost-saving potential from international sourcing and other sourcing levers: Relative importance and trade-offs. *International Journal of Physical Distribution & Logistics Management* 41 (3):315–36. doi:10.1108/09600031111123813.

Schulze-Horn, I.,Pulles, N. J., Schiele, H., & Scheffler, P. (2018). Using mechanism design theory in negotiations to improve purchasing performance. International Journal of Procurement Management, 11(6), 777-800.

Selten, R. 1991. Evolution, learning, and economic behavior. *Games and Economic Behavior* 3 (1):3–24. doi:10.1016/0899-8256(91)90003-W.

Simon, H. A. 1955. A behavioral model of rational choice. *The Quarterly Journal of Economics* 69 (1):99–118. doi:10.2307/1884852.

Simon, H. A. 1956. Rational choice and the structure of the environment. *Psychological Review* 63 (2):129–38. doi:10.1037/h0042769.

Simon, H. A. 1997. *Models of bounded rationality: Empirically grounded economic reason*, vol. 3. Cambridge, Massachusetts: The MIT press.

Singh, G., and C. M. O'Keefe. 2016. Decentralised scheduling with confidentiality protection. *Operations Research Letters* 44 (4):514–19. doi:10.1016/j.orl.2016.05.004.

Tan, S., and J. Brown. 2005. The World Café in Singapore: Creatinga learning culture through dialogue. *The Journal of Applied Behavioral Science* 41 (1):83–90. doi:10.1177/0021886304272851.

Tennenholtz, M. 2002. Game theory and artificial intelligence. In *Foundations and applications of multi-agent systems*, ed. M. d'Inverno, M. Luck, M. Fisher, and C. Preist, 49–58. Berlin, Heidelberg: Springer.

Varian, H. R. 2011. *Grundzüge der Mikroökonomik* [Fundamentals of microeconomics]. München: Oldenbourg Verlag.

Vos, F. G. S., P. Scheffler, H. Schiele, and P. Horn. 2016. Does global sourcing pay-off? A competitive dynamics perspective. *Journal of Purchasing and Supply Management* 22 (4):338–50. doi:10.1016/j.pursup.2016.07.002.

Wang, B., Y. Wu, and K. J. R. Liu. 2010. Game theory for cognitive radio networks: An overview. *Computer Networks* 54 (14):2537–61. doi:10.1016/j.comnet.2010.04.004.

Wynstra, J. Y. F. 2016. Past, present and future trends of purchasing and supply management: An extensive literature review. In *A journey through manufacturing and supply chain strategy research: A tribute to professor Gianluca Spina*, ed. E. Bartezzaghi, R. Cagliano, F. Caniato, and S. Ronchi, 199–228. Cham, Switzerland: Springer International Publishing.

Yan Chan, K., K. K. Fung Yuen, V. Palade, and Y. Yue. 2016. Artificial intelligence techniques in product engineering. *Engineering Applications of Artificial Intelligence* 47:1–2. doi:10.1016/j.engappai.2015.11.003.

Young, H. P. 1991. *Negotiation analysis*. Negotiation analysis, ed. H. P. Young. Ann Arbor: The University of Michigan Press.

Appendix

The following tables display all ideas that were generated during the World Café discussions. The columns "Points assigned by AI experts (in %)" and "Points assigned by PSM experts (in %)" display the relative amount of points assigned to the discussion points by the two expert groups respectively. The column "Total points assigned (in %)" shows the relative amount of points assigned to the discussion points aggregated over both expert groups. In the column "Cumulated total (in %)", the total points assigned are summed up.

Table A1. All results topic 1 (AI in the purchasing process).

Discussion points	Points assigned by AI experts (in %)	Points assigned by PSM experts (in %)	Total points assigned (in %)	Cumulated total (in %)
Cost-optimizing engineering	20%	14%	16%	16%
Analysis of cost breakdowns	7%	18%	14%	30%
Recognition of price patterns	4%	17%	12%	42%
Analysis of negotiation behavior	7%	13%	10%	52%
Supplier selection	13%	6%	8%	60%
Strategy optimization	9%	7%	8%	68%
Analysis of risk factors in buyer-supplier relationships	7%	7%	7%	75%
Development of supplier profiles	13%	0%	5%	80%
Analysis of suppliers' economic well-being	9%	3%	5%	85%
Analysis of process costs generated by suppliers	7%	1%	3%	88%
Predictive maintenance in tooling process	4%	3%	3%	92%
Development of documentation for purchasing steering committee	0%	4%	3%	94%
AI-based decision making in contract award process	0%	1%	1%	95%
Identification of opportunities for price optimization	0%	1%	1%	96%
Analysis of price development after contract awarding	0%	1%	1%	97%
Support of supplier onboarding process	2%	0%	1%	97%
Support of supplier rating process	0%	1%	1%	98%
Synchronization of deadlines in sourcing process	0%	1%	1%	99%
Identification of alternative suppliers	0%	1%	1%	100%
Negotiation bots	0%	0%	0%	100%
Support of problem resolution with suppliers	0%	0%	0%	100%
Development of process checklists	0%	0%	0%	100%

Table A2. All results topic 2 (AI in mechanism design-based negotiations).

Discussion points	Points assigned by AI experts (in %)	Points assigned by PSM experts (in %)	Total points assigned (in %)	Cumulated total (in %)
Analysis of negotiation behavior	27%	21%	23%	23%
Simulation of negotiations	15%	21%	19%	42%
Development of negotiation designs	18%	15%	16%	58%
Market analyses	9%	19%	15%	73%
Plausibility checks for cost breakdowns	9%	6%	7%	80%
Development of supplier profiles	15%	0%	6%	86%
Bonus/penalty evaluation	0%	10%	6%	93%
Analysis of suppliers' sentiment	6%	0%	2%	95%
Preparation for purchasing steering committee	0%	4%	2%	98%
Cross-functional coordination	0%	2%	1%	99%
Comparison of business cases	0%	2%	1%	100%
Plausibility checks for negotiation progress	0%	0%	0%	100%
Development of offer tool	0%	0%	0%	100%

Table A3: All results topic 3 (Implementation of AI in mechanism design-based negotiations).

Discussion points	Points assigned by AI experts (in %)	Points assigned by PSM experts (in %)	Total points assigned (in %)	Cumulated total (in %)
Negotiation simulations	15%	19%	17%	17%
Expert systems	8%	11%	9%	26%
Information seeking across systems	3%	16%	9%	36%
Heuristic mechanism design selection	15%	3%	9%	45%
Goal definition	10%	5%	8%	53%
Background information of suppliers	13%	0%	7%	59%
Controlling (classification learning)	8%	3%	5%	64%
Growing systems	8%	3%	5%	70%
Preparation for negotiations	3%	8%	5%	75%
Selection criteria for auction type	0%	8%	4%	79%
Combination of instruments	5%	3%	4%	83%
Challenge: data volume	5%	3%	4%	87%
Adjustment of data protection guidelines	3%	5%	4%	91%
Support of online negotiations	0%	5%	3%	93%
Storage capacity	0%	5%	3%	96%
Including human expert knowledge	3%	3%	3%	99%
Business intelligence/demand retrieval	3%	0%	1%	100%
Adjustment of rules during negotiation	0%	0%	0%	100%
Autonomous online negotiations	0%	0%	0%	100%
Analysis of past online negotiations	0%	0%	0%	100%
Support through experts	0%	0%	0%	100%